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Desirability Fuzzy Multiple criteria Optimization of Process Parameters in CNC Turning of GFRP/ Vinyl ester Composites

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Abstract

Although, Glass fiber reinforced vinyl ester resin is used for the production of many electrical components, automotive structural parts, sporting goods and high performance marine equipments, very little is known about its machining aspects. In this study, a hybrid multiple criteria optimization algorithm involving desirability index and fuzzy inference system coupled with Taguchi methodology is used to evaluate the optimal cutting parameters setting, in order to satisfy contradictory requirements of quality and productivity. Woven fabric based GFRP/ Vinyl ester tubes are finish turned using PCD cutting tool. Four process parameters, each at three levels are selected for the study viz. cutting tool nose radius, cutting speed, feed rate and depth of cut. Individual desirability indices of the three performance measures, viz. surface roughness, tangential cutting force and material removal rate are converted into a single multi-performance characteristics index (MPCI) using fuzzy inference system, which is then optimized using Taguchi analysis.

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Keywords: Multicriteria Optimization; GFRP/Vinyl ester; Woven fabric; Desirability index; Fuzzy inference system

1. Introduction

Machining aspects in the case of glass fiber reinforced plastics (GFRP) differ in comparison to that of metals. Machining of most of the homogeneous and ductile metals is characterized by shearing & plastic deformation and

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the formation of a continuous chip, whereas machining of GFRPs, is characterized by uncontrolled intermittent fracture. Oscillating cutting forces are typical, because of the intermittent fracture of the fibers (Jamal, 2009). Minimizing the cutting force is important as it affects cutting tool wear, tool life and stability of the machine tool. Quality and productivity are two important, but contradictory parameters, while performing machining operations. Quality mainly concerns with dimensional accuracy and surface roughness of the machined part, whereas productivity is directly related to Material Removal Rate (MRR) during machining. Quality of surface finish is inversely related to MRR. Hence, it becomes essential to evaluate the optimal cutting parameter settings, in order to satisfy contradictory requirements of quality and productivity.

Isik and kentli (2009) proposed a multiple criteria optimization approach using sensitivity. Minimizing cutting forces and maximizing the material removal were considered as objectives, while turning of unidirectional glass fiber reinforced polyester rods. Palanikumar et al. (2007) used grey relational grade & Taguchi method for minimizing tool wear, surface roughness and specific cutting pressure, while maximizing material removal. They carried out turning on GFRP/Epoxy composites using carbide (K10) tool. Balamugundan et al. (2012) used desirability function analysis to optimize surface roughness and delamination during milling of GFRP/Epoxy composites. Sait et al. (2009) optimized the turning process parameters of GFRP tubes for minimizing surface roughness, tool wear and cutting force. The GFRP pipes were made using the resin composition of isophthalic (50%) and vinyl ester (50%).They used desirability function analysis along with Taguchi technique for optimization.

It is observed that the machinability of composite materials is highly influenced by the type of fiber, type of resin, fiber orientation and method of manufacturing. The extant literature survey also reveals that woven glass fiber reinforced vinyl ester composites manufactured by hand lay-up process have not been widely explored for their machining characteristics, despite their wide applications. This study is an attempt to bridge this gap.

2. Methodology

The methodology used for this study is as shown below in Fig. 1.

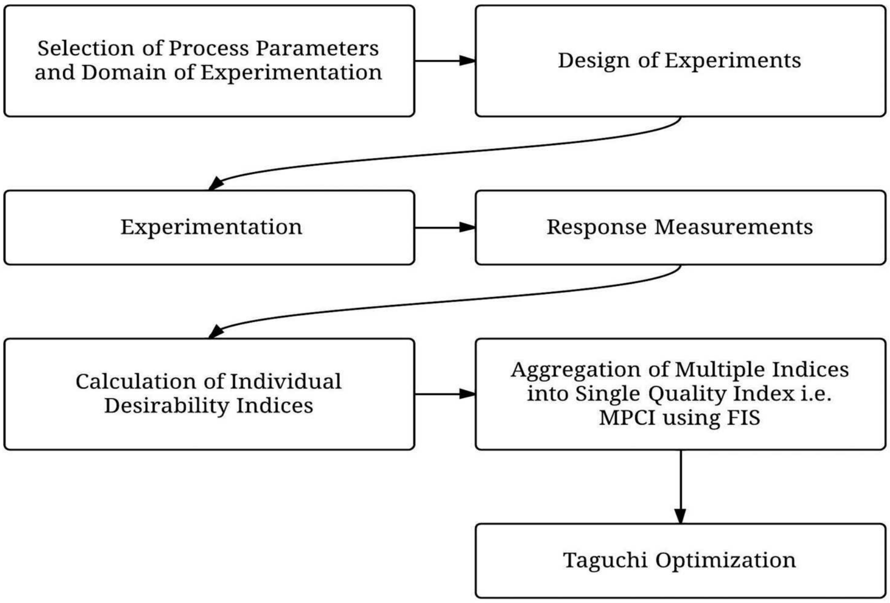

Fig. 1. Methodology used for the study.

2.1. Experimentation

The work material selected for this experiment is Glass fibre reinforced vinyl ester composite. The E-glass reinforcement is of woven fabric form, having following specifications. Type of weave: plain, weight: 180±5 gm/m^2 and of 0.18 mm thickness. The work specimens are tubular in shape 50 mm long, with inner diameter of 20 mm and outer diameter of 55 mm. They are manufactured using hand lay-up process and cured at room temperature. The volume fraction of the reinforcement is 70%. The resin produced by Crest Composites and Plastics Pvt. Ltd. with grade C'POL – 701/A is used for fabricating the specimens. The work specimens before & after machining are as per Fig. 2 (a & b). The cutting tool selected for turning is Poly Crystalline Diamond (PCD) insert of the fine grade. Three different types of inserts are used. They have ISO coding as CNMA 120404, CNMA 120408 and CNMA 120412. The tool holder is of WIDEX-ID1G with ISO coding, PCLNL 25X25 M12. The experiments are conducted on a Ace Jobber XL CNC lathe machine with the following specifications: swing over bed 500 mm, swing over carriage 260 mm, max. turning dia. 270 mm, max. turning length 400 mm, max. spindle speed 4000 rpm, spindle motor power 7.5 KW and Fanuc series Oi-TD Mate CNC controller. The machining tests are carried out without any coolant. The process parameters selected for the present work and their levels are as given in Table 1.

The experiments are planned using Taguchi's design of experiments (DOE). The nonlinear relationship among the process parameters, if it exists, can only be revealed if more than two levels of the parameters are considered (Byrne & Taguchi, 1987). Thus each selected parameter is analyzed at three levels. The total degrees of freedom (DOF) for four parameters, each at three levels are eight. Hence, a three level orthogonal array (OA) with at least eight DOF is to be selected. The L27 OA (DOF = 26) is thus selected for this case study. The factors are assigned to column no. 1, 2, 5 and 8 respectively. The unassigned columns are treated as error. Also the trials are carried out in random order. The work piece is mounted on specially designed mandrel, which is subsequently clamped by the lathe chuck. One repeat run is conducted for each of the 27 trials. The response measures selected are, surface roughness parameter Ra, tangential cutting force Fz and material removal rate MRR. The surface roughness parameter is measured using Taylor Hobson Talysurf-5 with Gaussian filter, cut-off length of 0.8mm, 5 cut-offs, and total traverse length 4mm. Data acquisition is accomplished by connecting this profiler to computer and using SESURF software. The tangential cutting force is measured with Kistler Piezo electric dynamometer of type-5233A with built in, charge amplifier up to 10 KN and a least count of 1mN. Data acquisition is accomplished by connecting this dynamometer to computer and using Kistler Dynoware type- 2825A software. The material removal rate is calculated as per Eq. (1), by measuring the weight of component before and after turning operation, with precision digital weighing machine and recording the machining time with a stop watch.

$$M.R.R. = \frac{W_i - W_f}{t_m}(gms/\sec) \qquad (1)$$

Where, W_i is the initial weight of work specimen in gms; W_f is the final weight of work specimen after machining in gms. and t_m is the machining time in sec. Table 2. shows L27 OA and the measured values of the three responses.

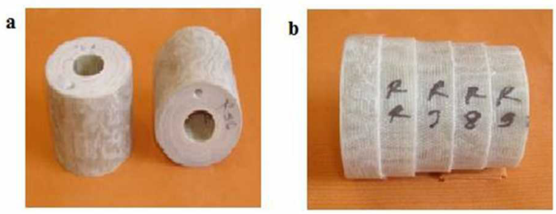

Fig. 2. (a) Work specimens before machining; (b) Work specimen after machining

Table 1. Selected process parameters and their levels.

Process parameters designation	Process parameters	Units	Levels		
			Level 1	Level 2	Level 3
A	Tool nose radius	mm	0.4	0.8	1.2
B	Cutting speed	m/min	120	160	200
C	Feed rate	mm/rev	0.05	0.15	0.25
D	Depth of cut	mm	0.6	1	1.6

Table 2. Taguchi's L27 OA and the measured mean values of the responses.

Trial No.	Design of experiments (coded)				Ra (microns)	Fz (N)	MRR (gms/sec)
	A	B	C	D			
1	1	1	1	1	0.970	8.530	0.117
2	1	1	2	2	2.209	28.795	0.103
3	1	1	3	3	2.158	74.085	1.167
4	1	2	1	2	1.814	10.010	0.189
5	1	2	2	3	1.931	46.065	1.000
6	1	2	3	1	3.555	18.785	1.000
7	1	3	1	3	2.203	15.640	0.419
8	1	3	2	1	2.364	16.910	0.500
9	1	3	3	2	3.112	43.705	1.500
10	2	1	1	1	2.733	6.665	0.102
11	2	1	2	2	2.058	27.115	0.400
12	2	1	3	3	2.292	73.575	0.917
13	2	2	1	2	1.709	10.220	0.241
14	2	2	2	3	2.335	46.720	1.000
15	2	2	3	1	4.270	24.980	0.750
16	2	3	1	3	2.245	15.780	0.407
17	2	3	2	1	2.753	14.710	0.500
18	2	3	3	2	2.970	39.795	1.000
19	3	1	1	1	1.386	6.210	0.078
20	3	1	2	2	2.125	23.820	0.818
21	3	1	3	3	3.301	66.010	0.833
22	3	2	1	2	2.141	11.335	0.186
23	3	2	2	3	3.061	43.900	1.054
24	3	2	3	1	3.491	21.695	0.500
25	3	3	1	3	1.391	15.775	0.394
26	3	3	2	1	1.551	14.590	0.583
27	3	3	3	2	2.324	38.085	0.500

2.2. Optimization

2.2.1. Desirability function approach

The desirability function approach for simultaneously optimizing multiple responses was originally proposed by Harrington (1965). Derringer and Suich (1980) later on popularized its usage by modifying it. This approach systematically transforms an estimated response $\hat{y}$ into a scale-free value of d_i. It assigns values from 0 to 1 to the possible value of each response, in which a number closer to unity is assigned to a more desirable response. If the value of the response falls beyond the prescribed tolerance rage, which is not desired, its desirability value is assumed as zero. In this study for surface roughness parameter R_a, and tangential cutting force F_z, Lower-the-better (LB) and for material removal rate M.R.R. Higher-the-better (HB) criteria have been selected.

While calculating individual desirability values using Lower-the-better (LB) criterion, the value of $\hat{y}$ is expected to be "lower the better". When it is less than a particular criteria value, the desirability value d_i equals to 1; if it exceeds a particular criteria value, the desirability value equals to 0. di varies within the range (0, 1). To find this kind of desirability function Eqs. (2-4) are used. Here, y_{min} denotes the lower bound of $\hat{y}$, whereas y_{max} represents the upper bound of $\hat{y}$ & r denotes the desirability function index, which is to be assigned previously by the decision maker. If the corresponding response is expected to be closer to the target, the index can be set to the larger value, and otherwise a smaller value.

$$\text{If } \hat{y} \le y_{min},\ d_i = 1 \tag{2}$$

$$\text{If } y_{min} \le \hat{y} \le y_{max},\ d_i = \left(\frac{\hat{y} - y_{max}}{y_{min} - y_{max}} \right)^r \tag{3}$$

$$\text{If } \hat{y} \ge y_{max},\ d_i = 0 \tag{4}$$

While calculating individual desirability values using Higher-the-better (HB) criterion, the value of $\hat{y}$ is expected to be higher the better. When it is greater than a particular criteria value, the desirability value d_i equals to 1; if it less then a particular criteria value, the desirability value equals to 0. di varies within the range (0, 1). To find this kind of desirability function Eqs. (5-7) are used. Here, y_{min} denotes the lower bound of $\hat{y}$, whereas y_{max} represents the upper bound of $\hat{y}$ & r denotes the desirability function index, which is to be assigned previously by the decision maker. If the corresponding response is expected to be closer to the target, the index can be set to the larger value, and otherwise a smaller value.

$$\text{If } \hat{y} \ge y_{max},\ d_i = 1 \tag{5}$$

$$\text{If } y_{min} \le \hat{y} \le y_{max},\ d_i = \left(\frac{\hat{y} - y_{min}}{y_{max} - y_{min}} \right)^r \tag{6}$$

$$\text{If } \hat{y} \le y_{min},\ d_i = 0 \tag{7}$$

The individual desirability values are usually aggregated to calculate the overall desirability using the following Eq. (8). Here, D_O is the overall desirability value, d_i is the individual desirability value of the i^{th} quality characteristic and n is the total number of responses. W_i is the weight for i^{th} attribute. Sum of all attribute weights should be equal to 1.

$$D_o = (d_1^{w_1} d_2^{w_2} d_3^{w_3} ......d_n^{w_n})^{1/\sum w_i} \quad (8)$$

However, the problem in treating overall desirability $D_{O,}$ as equivalent aggregated quality index is in assigning priority weights of various responses. Extant literature revealed that previous investigators have determined optimal setting of process parameters (Sait et al., 2009) by maximizing D_O within the experimental domain. Results obtained by such method can be inaccurate, as the exact value of priority weight to be assigned to each and individual responses is difficult to predict. Therefore, slight change in priority weight may shift the optimal setting, if these weights are found sensitive to predict the optima. To avoid this uncertainty, fuzzy inference system is used in the present study to couple individual desirability indices into a single performance index i.e. MPCI.

2.2.2. Fuzzy inference system

Fuzzy sets and systems were introduced by Prof. Lotfi A. Zedah in 1965. A fuzzy rule based system consists of four parts: Fuzzifier, knowledge base, inference engine and defuzzifier. Detailed analysis on fuzzy can be found in numerous literature (Zadeh 1976; Mendel 1992; Cox 1992). The four parts are described as follows.

2.2.2.1. Fuzzifier

The real world input in the crisp form, containing precise information about the specific parameter, is applied to the fuzzzifier. The fuzzifier converts this precise quantity to the form of imprecise quantity like 'large', 'medium', 'high' etc., with a degree of belongingness to it. Typically, the value ranges from 0 to 1.

2.2.2.2. Knowledge base

The main part of the fuzzy system is the knowledge base, in which both rule base and database are jointly referred. The database defines the membership functions of the fuzzy sets used in the fuzzy rules, whereas the rule base contains a number of fuzzy IF-THEN rules. The rules set used for the present fuzzy inference system are given in Table 3.

2.2.2.3. Inference engine

The inference system or the decision-making unit performs the inference operations on the rules. It handles the way in which the rules are combined. In general two most popular fuzzy inference systems are available: Mamdani fuzzy model and Sugeno fuzzy model. Mamdani fuzzy model is based on the collections of IF-THEN rules with both fuzzy antecedent and consequent predicts. The benefit of this model is that the rule base is generally provided by an expert and hence to a certain degree, it is translucent to explanation and study. Because of its ease, Mamdani model is still the most commonly used technique for solving many real world problems.

2.2.2.4. Defuzzifier

The output generated by the inference block is always fuzzy in nature. A real world system will always require the output of the fuzzy system to be crisp or in the form of real output. The job of the defuzzifier is to receive the fuzzy input and provide real world output. In operation, it works opposite to the input block.

Table 3. Rule set used for the FIS.

Rule	IF D_1 (Ra) is	AND D_2 (Fz) is	AND D_3 MRR) is	THEN MPCI is	Rule	IF Ra is	AND Fz is	AND MRR is	THEN MPCI is
R1	Low	Low	Low	very low	R33	High	High	Low	high
R2	Low	Low	Medium	very low	R34	Medium	Low	Medium	low
R3	Low	Low	High	low	R35	High	Low	Medium	medium
R4	Low	Medium	Low	very low	R36	Low	Medium	Medium	low
R5	Low	Medium	Medium	low	R37	High	Medium	Medium	high
R6	Low	Medium	High	medium	R38	Low	High	Medium	medium
R7	Low	High	Low	low	R39	High	High	Medium	very high
R8	Low	High	Medium	medium	R40	Low	Low	High	low
R9	Low	High	High	high	R41	Medium	Low	High	medium
R10	Medium	Low	Low	very low	R42	Low	Medium	High	medium
R11	Medium	Low	Medium	low	R43	Medium	Medium	High	high
R12	Medium	Low	High	medium	R44	Low	High	High	high
R13	Medium	Medium	Low	low	R45	Medium	High	High	very high
R14	Medium	Medium	Medium	medium	R46	Medium	Low	Low	very low
R15	Medium	Medium	High	high	R47	Medium	Low	Medium	low
R16	Medium	High	Low	medium	R48	Medium	Low	High	medium
R17	Medium	High	Medium	high	R49	High	Low	Low	low
R18	Medium	High	High	very high	R50	High	Low	Medium	medium
R19	High	Low	Low	low	R51	High	Low	High	high
R20	High	Low	Medium	medium	R52	Low	Medium	Low	very low
R21	High	Low	High	high	R53	Low	Medium	Medium	low
R22	High	Medium	Low	medium	R54	Low	Medium	High	medium
R23	High	Medium	Medium	high	R55	High	Medium	Low	medium
R24	High	Medium	High	very high	R56	High	Medium	Medium	high
R25	High	High	Low	medium	R57	High	Medium	High	very high
R26	High	High	Medium	very high	R58	Low	High	Low	low
R27	High	High	High	very high	R59	Low	High	Medium	medium
R28	Medium	Low	Low	very low	R60	Low	High	High	high
R29	High	Low	Low	low	R61	Medium	High	Low	medium
R30	Medium	Medium	Low	low	R62	Medium	High	Medium	high
R31	High	Medium	Low	medium	R63	Medium	High	High	very high
R32	Medium	High	Low	medium					

In this study, an attempt is made to use fuzzy system to estimate the MPCI, when values of d_i are given as inputs to the system. The given model would be a MISO (Multi Input and Single Output) model as shown in Fig. 3.

The number of input variables (d_i) obtained in desirability function analysis & labelled as d_1, d_2, d_3, etc. are used as inputs. In three inputs (d_i) and one output (MPCI) system, both the inputs and the output are taken in the form of linguistic format. A linguistic variable is a variable, whose values are words or sentences in a natural or man-made language. For example, d_1 = {low, medium, high}, d_2 = {low, medium, high}, and d_3 = {low, medium, high). The output variable (MPCI) is similarly divided into MPCI = {very low, low, medium, high, very high}. Fuzzy values are determined by the membership functions, however so far there has been no standard method for choosing the proper shape of the membership functions for control variables. In the proposed model Gaussian type membership functions are used for input as well as output variable, as shown in Fig. 4 a & b respectively. In this proposed model, centriod of area (COA) method of defuzzification is used for determining the output. This crisp value is the MPCI. Individual desirability values of the responses and MPCI values are as shown in Table 4.

Table 4. Individual desirability values of the responses and MPCI.

Sr. No.	Individual desirability values of the responses			MPCI	S/N ratio
	D_1 (Ra)	D_2 (Fz)	D_3 (MRR)		
1	1.000	0.966	0.027	0.621	-4.13817
2	0.625	0.667	0.017	0.35	-9.11864
3	0.640	0.000	0.766	0.441	-7.11123
4	0.744	0.944	0.077	0.601	-4.42251
5	0.709	0.413	0.648	0.563	-4.98983
6	0.217	0.815	0.648	0.522	-5.64659
7	0.626	0.861	0.240	0.565	-4.95903
8	0.577	0.842	0.297	0.604	-4.37926
9	0.351	0.448	1.000	0.689	-3.23562
10	0.466	0.993	0.016	0.498	-6.05541
11	0.670	0.692	0.226	0.444	-7.05234
12	0.599	0.008	0.590	0.302	-10.3999
13	0.776	0.941	0.114	0.609	-4.30765
14	0.586	0.403	0.648	0.519	-5.69665
15	0.000	0.723	0.472	0.358	-8.92234
16	0.614	0.859	0.231	0.556	-5.0985
17	0.460	0.875	0.297	0.623	-4.11024
18	0.394	0.505	0.648	0.516	-5.74701
19	0.874	1.000	0.000	0.62	-4.15217
20	0.650	0.741	0.520	0.611	-4.27918
21	0.294	0.119	0.531	0.296	-10.5742
22	0.645	0.924	0.076	0.523	-5.62997
23	0.366	0.445	0.686	0.526	-5.58029
24	0.236	0.772	0.297	0.495	-6.1079
25	0.872	0.859	0.222	0.599	-4.45146
26	0.824	0.877	0.355	0.691	-3.21044
27	0.590	0.530	0.297	0.445	-7.0328

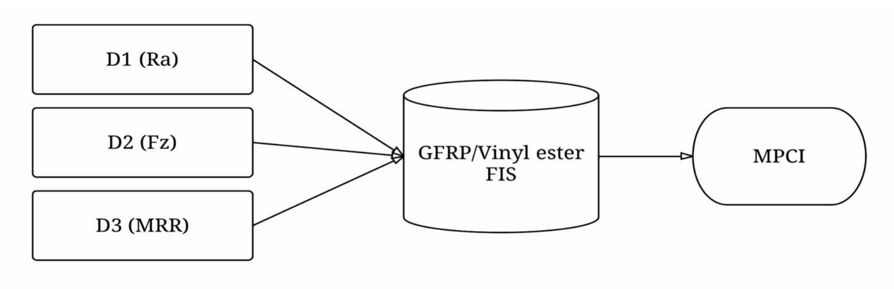

Fig. 3. The FIS model

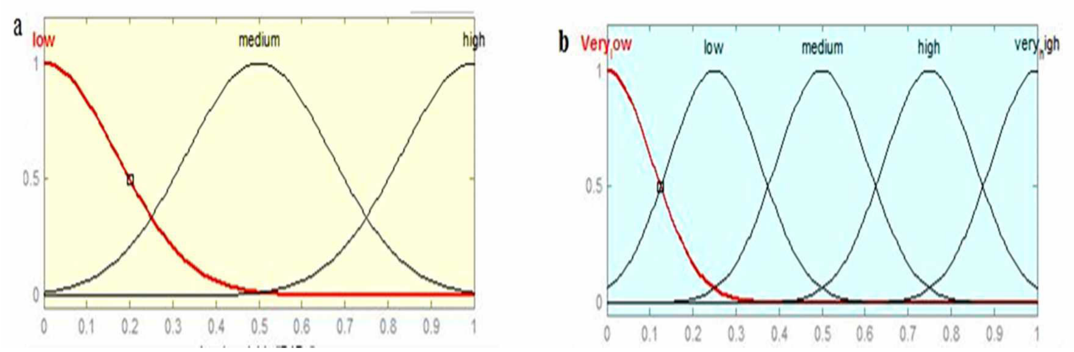

Fig. 4. (a) Membership functions of the inputs; (b) Membership functions of the output MPCI.

2.2.3. Taguchi optimization

To determine the optimal parameter settings, it is required to find out the highest MPCI. Optimization (maximization) of MPCI has been carried out using Taguchi method. Taguchi method converts response value into corresponding S/N ratio. The Signal-to-Noise (S/N) ratio is the ratio of mean to deviation of the response from targeted value. Therefore, in Taguchi analysis the optimal parametric combination is determined by incorporating Higher-the better criteria of the response S/N ratio. Optimal parametric combination has been evaluated from the plot in Fig.5. Optimal setting becomes: A1B3C1D1. The estimated mean of the response characteristic S/N ratio (η) can be computed by using the following Eq. (9), (Madhav S. Phadke, 1989). Where $\bar{\eta}$ = overall mean of S/N ratio (η) for MPCI, B_3 = average value of S/N ratio (η) for MPCI at third level of speed and C_1 = average value of S/N ratio (η) for MPCI at first level of feed. B & C are the most significant factors, affecting the S/N ratio (η) for MPCI.

$$\eta_{opt} = \bar{\eta} + (B_3 - \bar{\eta}) + (C_1 - \bar{\eta}) \tag{9}$$

Predicted value (S/N Ratio) of MPCI becomes−3.10107 (highest among all entries of values in Table 4.) whereas in confirmatory test it has been computed as−2.9058. So quality has improved by using this optimal setting (increment of S/N ratio).

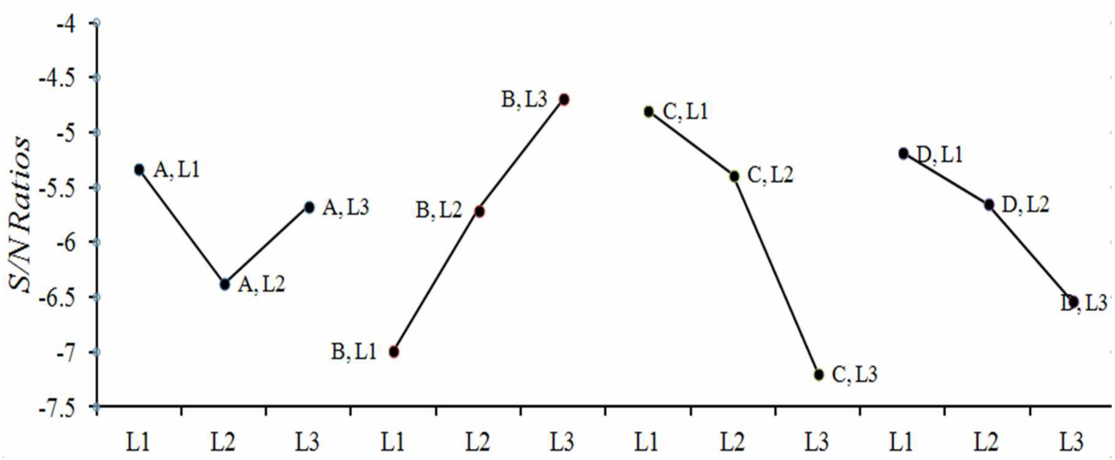

Fig. 5. Main effects plot of S/N ratios for MPCI

3. Conclusion

In this study, the fuzzy rule based model has been developed using three input variables and one output variable i.e. MPCI. By this way, a multi-response optimization problem has been converted into an equivalent single objective optimization problem which has been solved by Taguchi philosophy. The proposed procedure is simple and effective in developing a robust finish turning process for GFRP/Vinyl ester composites. The proposed approach converts numerical response into a linguistic term so that the issue of response correlation can be avoided.

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